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Power Management Strategy for Plug-in Hybrid Electric Vehicles using Engine Switching Status

Yi-Min Hsieh** and Yen-Chen Liu*

Keywords: Plug-in hybrid electric vehicles (PHEV), engine on/off status, power management strategy, model predictive control (MPC), velocity prediction.

ABSTRACT

Plug-in hybrid electric vehicle (PHEVs) is a kind of hybrid electric vehicles (HEV) that has a large capacity battery to satisfy the requirement of the distance for commuters. A parallel PHEV has two kinds of power source, internal combustion engine (ICE) and electric motor (EM), so that a control strategy to split the driving power to ICE and EM is important to have a superior fuel economy. In this paper, we propose a rule-based and an optimization-based strategies to guarantee fuel consumption and vehicle performance by deciding engine on/off status. For the developed rule-based method, a proportional algorithm is developed with the information of trip distance to generate a dynamic threshold which decides when to turn the engine on. If the engine is turned on, it is operated at the best efficiency with the desired of vehicle speed. Subsequently, an optimization-based method by using model predictive control (MPC) is addressed for PHEVs with guaranteed battery trajectory while minimizing fuel consumption. Both the control strategies can improve fuel economy comparing with other strategies, and the proposed methods are considered and studied via numerical simulations.

INTRODUCTION

Although vehicles have become the most popular and significant transportation, traditional vehicles that continue on burning fossil fuels have resulted in inefficiency at high operating costs and emissions. Moreover, the conventional vehicles using fossil fuel is one of the reasons that aggravates air pollution, global warming, and respiratory infection (Emadi *et al.*, 2003; Frank, 2007; Tanoue *et al.*, 2008). In order to ensure energy supply, preserve environment, and achieve continuous economic growth, electric vehicles (EVs) and hybrid electric vehicles (HEVs) have been developed for higher vehicle efficiency with decreasing of fuel consumption (Taghavipour *et al.*, 2012; Kimura *et al.*, 2005; Williamson *et al.*, 2006; Hwang *et al.*, 2015; Yin and Hu, 2014). Such green vehicles take the advantages of clean energy such as electrical energy to propel vehicles and reduce fuel cost and emissions simultaneously. To overcome EVs from lower cruising endurability due to limited battery capacity, HEVs provide not only sufficient cruising endurability but also satisfactory fuel economy.

HEVs can be divided into extended-range electric vehicles (EREVs) and blended HEVs (Wirasingha and Emadi, 2011; Tanoue *et al.*, 2008; Emadi *et al.*, 2003; Qi *et al.*, 2018). For EREVs, vehicles are operated by using electrical energy from a battery system until the state-of-charge (SOC) reaches a certain level. When the battery system drops to minimally acceptable SOC level, such vehicles are operated on extended-range-mode where engine is turned on to charge battery. Although blended HEVs can provide higher power from mingling electric motor with internal combustion engine (ICE), HEVs might not be able to cover entire driving distance because the battery state-of-charge is restricted (Tanoue *et al.*, 2008; Frank, 2007; Moon *et al.*, 2006). Therefore, plug-in hybrid vehicles (PHEVs), which equipped with a large battery pack and a high-power motor, gradually become a better option for green vehicles (Chen *et al.*, 2014a; Cai *et al.*, 2017; Frank, 2007; Wirasingha and Emadi, 2011). Moreover, PHEVs can be charged by electrical grid, so that they can make good use of the electrical energy from the power plant. Hence, it is more environmental-friendly since the energy from the power plant is more efficiency with less emissions.

Extensive research and development have been conducted on PHEVs from mechanical design, power management, and control strategy (Chen *et al.*, 2014a; Chen *et al.*, 2014b; Gong *et al.*, 2008; Hsieh and Liu, 2015; Khayyer *et al.*, 2012; Taghavipour *et al.*, 2012;

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* Associate Professor, Department of Mechanical Engineering, National Cheng Kung University, Tainan 70101, Taiwan

** Graduate Student, Department of Mechanical Engineering, National Cheng Kung University, Tainan 70101, Taiwan

Zhang *et al.*, 2012). PHEVs can take the advantage of "plug-in" to reduce fuel cost and emissions of vehicles in operation. For commuters, if the commuting distance is shorter than cruising endurability of PHEVs, then PHEVs can be operated similar to EVs in that they use only the energy from battery system (Chen *et al*., 2014a; Hsieh and Liu, 2015; Taghavipour *et al.*, 2012). Thus, PHEVs can charge from plug-in power during the night. In other words, under the circumstances of short distance for daily commute, fuel consumption is not needed. With the property of charging during the night, the utilization of power plants can be improved. Moreover, PHEVs can also act like a backup power, which can be used in a trip or emergency situations.

Although PHEVs have the aforementioned advantages, how to mingle the electric power and engine power to provide better driving performance and ensure minimum fuel consumption is a crucial problem (Chen *et al*., 2014b; Gong *et al*., 2008; Wu *et al*., 2014; Zhang *et al*., 2012). The main aim of control strategy is to enable the PHEVs to have a good performance and fuel economy, which can be achieved by coordinating the power between EM and ICE. The driving modes of PHEVs can be classified into three kinds according to the state of charge (SOC) as shown in Figure 1 (Matthe and Eberle, 2014; Zhang et al., 2012). They are charging-sustaining mode (CS mode), charging-depleting mode (CD mode), and electric vehicle mode (EV mode). The CS mode lets vehicles maintain the SOC in a constant level, and the vehicles operating in CD mode depletes the SOC in a certain rate. The EV mode means that vehicles operate similar to electric vehicle which use no ICE power to drive vehicles or charge the battery. PHEVs usually start in CD mode and switch to CS mode after the battery has reached its minimum SOC threshold.

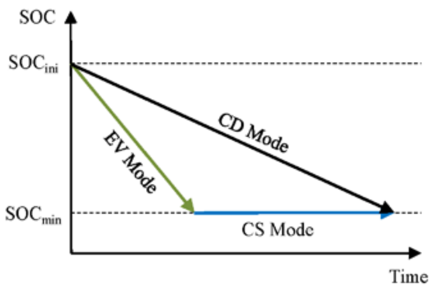


Fig. 1. Driving modes of PHEVs (Wirasingha and Emadi, 2011).

Several strategies for PHEV power management have been proposed in technical literature recently. Numerical solutions and algorithms such as dynamic programming (DP) (Chen *et al.*, 2014c), Pontryagin's minimum principle (PMP) (Chen *et al*., 2014a), genetic algorithm (GA) (Chen *et al.*, 2014b) are used to solve the optimization problem. Although the aforementioned methods can improve the fuel economy, it is subject to heavy computing burden or non-causality that make the strategies too difficult to implement in real-time. In Zhang *et al.* (2012) and Zhang *et al.* (2011), the authors analyzed the powertrain and found the engine-on threshold with different methods. In Gong *et al.* (2008) and Wu *et al.* (2014), they investigated trip models to approximate the real world driving cycles. In Feng *et al.* (2015), and Zhang and Vahidi (2012), the authors applied the equivalent consumption minimization strategy (ECMS) to find the powertrain state. A two-level controller for power management of PHEVs based on cycle energy estimation was presented to lower computational load (Marcos and Bordons, 2012). Recently, the control strategy using the remain travel distance with Global Position System (GPS) information was developed for the energy optimization of PHEVs (Liu and Murphey, 2014).

In addition to the previous methods, model predictive control (MPC) seems to be a proper method to exploit the potentials of modern concepts and to fulfill the automotive requirements (Borhan *et al*., 2009; Feng *et al.*, 2015; Sun *et al.*, 2015). Since most of vehicle power system can be stated in the form of a constrained multi-input multi-output optimal control problem, MPC can provide an approximated solution of this class of problems. MPC-based method, which takes system dynamics into account, is investigated to deal with the optimization control problem along a finite receding horizon. Compared to numerical solutions, MPC can offer less computationally expensive solutions and enable real-time implementation. Several applications such as Taghavipour *et al.* (2012) and Borhan *et al*. (2009) of MPC to HEVs have been investigated previously. In Borhan *et al.* (2012), the authors considered a nonlinear MPC and solved the MPC by PMP to improve the fuel economy. In Zhang and Shen (2014) and Zhang *et al.* (2014), the authors also considered a nonlinear MPC and PMP, but used the Continuous/GMRES algorithm to reduce computation time. In Sun *et al.* (2015), the authors developed the velocity predictors for MPC to use and solved the MPC by DP.

In this paper, we proposed two control strategies to achieve power management for parallel PHEVs to improve fuel economy by determining the timing of engine on/off status. The first method is a rule-based strategy that utilizes trip distance and battery state to tune the engine on/off threshold. If the required power is larger than the engine on/off threshold, then the engine is turned on to provide assisting power for PHEVs. The second method is an optimization-based strategy that decides the on/off status of internal combustion engine directly by using MPC and DP. Since more driving information are required in the second method, the optimization-based strategy can provide a better fuel consumption. Simulation results by using ADVISOR with a commercial vehicle model for different standard driving cycles are presented to validate the performance of the proposed methods.

PROBLEM FORMULATION AND VEHICLE MODEL

Problem Formulation

The main aim of control strategy for PHEVs is to ensure a good performance with fuel economy, which can be achieve by coordinating the power between electric motor and internal combustion engine. In general, the main power source of HEVs is ICE, whereas having a large batter pack electric motor is the main power source for PHEVs. The operation of PHEVs can be classified into three kinds of mode according to the state of charge (SOC) of the energy-storage system (ESS), depending on the energy source providing the propulsion power. These three modes are EV mode, CD mode, and CS mode.

PHEVs in EV mode operate only by electric motor and use energy from the electric machine until SOC decreases to a predefined minimum value, SOC_{min}. When SOC of PHEVs reaches SOC_{min}, vehicles can no longer be driven by using only electric energy so that the engine has to start to drive the vehicle and supply power to charge battery in ESS when required. This is called CS mode, and the vehicle is operating by engine with/without electric motor with the constraint of maintaining a constant battery SOC to SOC_{min}. CD mode is when PHEVs in operation using energy primary from electric motor with secondary energy from engine to guarantee SOC drop to the predefine minimum value, SOC_{min}, in the end of trip distance. It has been demonstrated extensively that PHEVs operating in CD mode can provide the best fuel efficiency improvement comparing to other driving mode (Zhang *et al.*, 2011). Therefore, how to achieve optimized CD operations in PHEVs for an entire trip is one of the most significant problems in developing control strategy for PHEVs.

The objective of this paper is to develop power management and control strategy for PHEVs to operate in CD mode, which means that the SOC decreases to SOC_{min} only when vehicles arrive at the end of a given trip. Since the engine in CD mode is only a secondary energy to provide supportive driving power to PHEVs, the proposed control strategy is developed based on the on/off status of engine. In this manner, PHEVs can be driven mainly by electric motor, and the engine is turned on only when the required power is excess a predefined value. Engine on/off strategy has been previously studied by Zhang *et al.* (2012); however, the engine was not operated in hight efficiency region while the hybrid vehicle requires power from ICE. Moreover, the engine-turn-on threshold is predefined and fixed, which limits the flexibility and fuel efficient of PHEVs. Therefore, two control strategies: rule-based and optimization-based managements, are developed in paper to achieve the objective of CD mode operation with better fuel efficiency. The proposed power management is designed based on engine status, S_{eng}, for engine to supply power when higher driving power is required. Moreover, when the engine turns on, the proposed strategy can guarantee that engine is operated in higher efficiency so that fuel consumption is enhanced.

Vehicle Model

PHEVs have a battery pack of high energy density that can externally charged, so that PHEVs can be operated by only electric power for a longer range, which is named all-electric range (AER) (Wu *et al.*, 2014; Wirasingha and Emadi, 2011). Based on the powertrain architecture, PHEVs can be classified into two types, which are extended range electric vehicle (EREVs) and blended-mode PHEVs (Wirasingha and Emadi, 2011). With full-sized tracking motor, EREVs can perform electric vehicle driving without assisting power from engine if state-of-charge (SOC) of electric storage system (ESS) is above a certain threshold. If SOC is insufficient to provide pure electric driving, then engine turns on to charge ESS for longer driving distance.

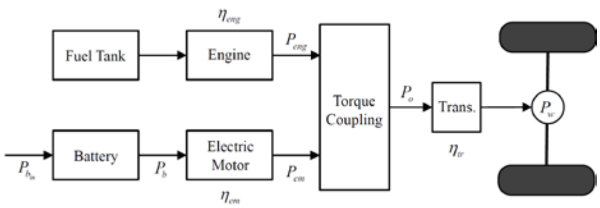


Fig. 2. Parallel PHEV powertrain architecture.

Contrarily, parallel PHEVs require less electric driving capability with additive engine power to achieve higher power or torque during operations. Although parallel PHEVs are more complex with higher dimensions, system performance, drivability, and fuel consumption can be achieved for such hybrid vehicles to operate engine more efficiently (Wirasingha and Emadi, 2011; Zhang *et al.*, 2012). In this paper, two power management control strategies are developed for blended-mode PHEVs, as shown in Figure 2, where P_{eng} is the power from engine with efficiency η_{eng}, $P_{b_{in}}$ is the input power to charge battery, P_b is the battery power, P_{em} is electric power with the electric motor efficiency η_{em}, P_o is the current power entering the transmission, η_{tr} is the transmission efficiency, and P_w is power for driving wheels.

The vehicle dynamics of blended-mode PHEVs is addressed in this section. According to the vehicle dynamics with the consideration of rolling resistance and aerodynamic drag on the vehicle in the absence of slippage, the driving torque T_{drive} is described by

$$T_{drive} = R_w(m\dot{v} + mgC_r\cos\theta + mg\sin\theta + 0.5\rho A_f C_d v^2), \tag{1}$$

where v is vehicle velocity, R_w is wheel radius, m is vehicle mass, g is gravitational acceleration constant,

C_r is rolling resistance coefficient, θ is road slope, ρ is air density, A_f is front area of the vehicle, and C_d is drag coefficient. The relationship between vehicle velocity and wheel rotational speed is given as

$$v = \omega_w R_w, \tag{2}$$

where ω_w is the rotational velocity of wheels. At the wheel axle, the balance of torques between engine torque T_{eng} and motor torque T_{em} to T_{drive} is given as

$$T_{drive} = \eta_{eng} S_{eng} N_{eng} T_{eng} + \eta_{em} N_{em} T_{em}, \tag{3}$$

where N_{eng} and N_{em} denote the gear ratio from final drive to the torque coupler for engine and motor, respectively, T_{eng} and T_{em} are engine torque and motor torque, and S_{eng}=\{0,1\} denotes the engine status, where S_{eng}=1 means the engine turns on, and S_{eng}=0 denotes that the engine is off. Based on rotational velocity of wheels, the relationship between wheel, engine, and electric motor are

$$\omega_w = \frac{1}{N_{eng}} \omega_{eng} = \frac{1}{N_{em}} \omega_{em}, \tag{4}$$

where ω_{eng} and ω_{em} denote the rotational velocity of output shaft of engine and electric motor, respectively.

The SOC of a battery in ESS can be modeled by an internal resistance model that is given as

$$\frac{dSOC}{dt} = \frac{-V_{oc} + \sqrt{V_{oc}^2 - 4P_b R_b}}{2R_b Q_b}, \tag{5}$$

where V_{oc} is the battery open-circuit voltage, R_b is the battery internal resistance, Q_b is the battery capacity, and P_b is the battery power which is a function of motor torque and speed given as following

$$P_b = \text{motor}_{\text{power}}(T_{em}, \omega_{em}). \tag{6}$$

For internal combustion engine (ICE) system, the fuel consumption is measured by the flow rate of fuel mass $\dot{m}_f$, which is dependent on the engine torque and engine speed as described in the equation that

$$\frac{dm_f}{dt} = \text{fuel}(T_{eng}, \omega_{eng}). \tag{7}$$

The fuel function will be utilized in the analysis of the proposed power management and further implement in various control strategies addressed in this paper.

POWER MANAGEMENT WITH ENGINE ON-OFF STATUS

Rule-Based Proportional Control Strategy (RBPCS)

The first power management is developed based on a rule-based control strategy under the assumption that the trip length d_{total} is known in advance. Generally, the trip length d_{total} can be easily obtained from GPS navigation system, and the total energy E_{total} is available from the analysis of driving cycle. If d_{total} is shorter enough so that the required energy for an entire trip E_{total} is less than the available energy from the ESS, then the vehicle can be operated in only EV mode and no power management is needed. Therefore, we consider only the situation that E_{total} is larger than the entire energy can be provided by ESS via electric motor.

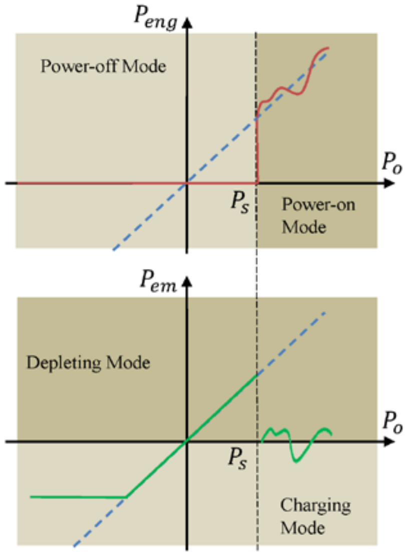


Fig. 3. Engine on/off status for the proposed rule-based power management, where P_o= P_{eng}+ P_{em}.

From the powertrain architecture of PHEVs in Fig. 2, the power required by the vehicle for a trip is given as

$$\eta_{tr} P_o = \eta_{tr} (P_{eng} + P_{em}) = F_{drive} v, \tag{8}$$

where F_{drive} is the driving force. The engine output power and electric motor output power are given as

$$P_{eng} = T_{eng} \omega_{eng}, \quad P_{em} = T_{em} \omega_{em}. \tag{9}$$

From the electric motor in Fig. 2, the battery output is given as

$$P_b = \frac{1}{\eta_{em}} P_{em} = V_{oc} I. \tag{10}$$

From energy storage system (ESS), the change of SOC level for a trip in CD mode is given as

$$\Delta SOC = SOC_{current} - SOC_{min} = \frac{\int I(t)dt}{Q_b}, \tag{11}$$

where Q_b is the capacity of the battery. By taking the time-derivative of (11) with SOC$_{min}$ as a constant, the current at each time instance is

$$I = Q_b \frac{dSOC}{dt}. \tag{12}$$

By substituting (12) into (10), the power supplied by battery to drive electric motor at each time instance is

$$P_b = V_{oc} Q_b \frac{dSOC}{dt}, \tag{13}$$

where the energy of battery can be obtained from E_b = $V_{oc}Q_b$. Subsequently, with the assumption that η_{tr} =1 for simplicity, combining (8), (10), and (13) gives that

$$P_{eng} = P_o - P_{em} = P_o - \eta_{em} P_b = P_o - \eta_{em} E_b \frac{dSOC}{dt}. \tag{14}$$

By taking the summation of power in (14) for an entire trip, the relationship between total driving power, engine power, and electric motor power can be obtained and given as

$$\sum P_{eng}(k) = \sum P_o(k) - \eta_{em} E_b \Delta SOC(k) := E_{eng,total}. \quad (15)$$

Algorithm 1. Rule-based proportional control strategy

```
d_total ⇐ Total trip distance, P_sini[0] ⇐ P_sini
SOC_current [0] ⇐ SOC_ini, P_o[0] ⇐ P_o,ini
P_bin [0] ⇐ 0, v[0] ⇐ v_ini, d_covered [0] ⇐ 0, i ⇐ 0
repeat
    P_s[i] = P_sini[i] + K_p[1-K_c(d_total − d_covered[i])/
    (SOC_current [i] − SOC_min)]
    if P_o[i] > P_s[i] then S_eng ⇐ 1
        if P_eng[i] > P_o[i] subject to max(η_eng(v([i])) then
            if SOC_current [i] ≥ SOC_max then
                P_eng ⇐ P_eng[i]
                    subject to max(η_eng(v([i]))
                    and P_eng[i] < P_o[i]
                P_em ⇐ P_o[i] − P_eng[i], P_bin ⇐ 0
            else
                P_eng ⇐ P_eng[i]
                    subject to max(η_eng(v([i]))
                P_bin ⇐ P_eng[i] − P_o[i], P_em ⇐ 0
            end if
        else
            if SOC_current [i] ≤ SOC_min then
                P_eng ⇐ P_eng[i]
                    subject to max(η_eng(v([i]))
                    and P_eng[i] > P_o[i]
                P_bin ⇐ P_eng[i] − P_o[i], P_em ⇐ 0
            else
                P_eng ⇐ P_eng[i]
                    subject to max(η_eng(v([i]))
                P_em ⇐ P_o[i] − P_eng[i], P_bin ⇐ 0
            end if
        end if
    else S_eng ⇐ 1
        P_eng ⇐ 0, P_bin ⇐ 0, P_em ⇐ 0
    end if
    P_o ⇐ P_eng + P_em
    i ⇐ i+1
until termination
```

Consequently, if the PHEV is operated in CD mode that the SOC level arrives at SOC_{min}, the total energy from engine should be equal to $E_{eng,total}$. If the engine generates energy more than $E_{eng,total}$, then the SOC level will not reach SOC_{min} in the end of the trip. Otherwise, if $\Sigma P_{eng}(k)$ is less than $E_{eng,total}$, then the vehicle will be driven in CS mode when SOC approached SOC_{min}. Either of the above situations will have worse fuel consumption comparing to CD mode (Zhang *et al.*, 2012; Wirasingha and Emadi, 2011).

Since the electric motor in PHEV can provide more energy than HEV, the engine only needs to be turned on to assist driving the vehicle if the required power is higher than a certain value. Therefore, to ensure PHEVs driving in CD mode, we proposed an engine on-off status strategy by designing the threshold to switch the on/off status of the engine. By combining the aforementioned formulation, the power management strategy is to design an engine on/off threshold, P_s. If the required power P_o at an instance is less than P_s, then the engine is turned off and the vehicle is driven purely by the electric motor. During the same trip, if the vehicle driving power P_o is larger than P_s, then the engine is turned on to assist driving the vehicle. Meanwhile, the engine operates in the desired speed with best efficiency so that the fuel consumption is guaranteed. The power of engine and electric motor for the proposed rule-based power management are shown in Figure 3. It is noted that $P_o = P_{eng} + P_{em}$, and engine supplies power to the vehicle only when required P_o is larger than P_s the power threshold.

In the rule-based control strategy, the engine on/off threshold, P_s, is decided by a proportional control law that is given as

$$P_s = P_{s_{ini}} + K_p\left[1 - K_c \frac{d_{total} - d_{covered}}{SOC_{current} - SOC_{min}}\right], \quad (16)$$

where $P_{s_{ini}}$ is an approximated initial threshold, K_p is a positive proportional gain, K_c is a constant control gains, d_{total} is the distance for an entire trip, $d_{covered}$ is the covered trip distance, and $SOC_{current}$ is the current SOC level. The main objective is to ensure that $SOC_{current}$ approaches SOC_{min} when $d_{covered}$ is equal to d_{total}.

In order to reduce fuel consumption and ensure SOC decreases to SOC_{min} in the end of a desired trip, the power threshold, P_s, is designed based on a proportional control strategy (16). With the proposed threshold for engine status, the pseudo-code of the control strategy for power management is addressed in Algorithm 1. As shown in Fig. 3, the vehicle is driven purely by electric motor if P_o is less than P_s, the power threshold to turn engine on. If the demand vehicle power P_o is larger than the threshold P_s, then the vehicle needs to check the power of the engine with best fuel efficiency and SOC level at the desired shaft velocity ω_{eng}. Since SOC cannot excess SOC_{max}, the maximum value of SOC, if the power at the best efficiency is larger than P_o, then the engine is operated at the optimized η_{eng} subject to $P_{eng} < P_o$. In this case, the power requires from electric motor is $P_o - P_{eng}$, while the engine is operated with less fuel consumption. If P_{eng} at the best η_{eng} with $SOC_{current}$ less than SOC_{max}, then the engine is operated at the best efficiency and the excessive power will be utilized to charge the battery. If the required vehicle power is large than P_s while P_{eng} at the best η_{eng} is less than P_o, then the engine is operated at the best efficiency if $SOC_{current}$ is larger than SOC_{min}. However, if $SOC_{current}$ is less than or equal to SOC_{min}, the engine needs to generate extra power to charge battery to avoid damage battery and ESS. Thus, the engine is operated in the best η_{eng} subject to P_{eng} larger than P_o so that the extra power can be provided to charge the battery. The performance of this control strategy is validated in Section 4.

Optimization-Based Prediction Control Strategy (OBPCS)

In order to optimize the fuel consumption and driving performance of PHEVs, we proposed an optimization-based prediction control strategy in this section by utilizing engine on/off status. The concept of this method is similar to RBPCS in the previous section by designing the engine power threshold P_s. Nevertheless, the optimum power threshold P_s is determined and obtained without using a proportional control. The optimization method is implemented by model predictive control (MPC) and dynamic programming (DP).

The general design objective of MPC is to compute a trajectory of a future input to optimize the future behavior of the output of a control system. The optimization is performed within a limited time window based on the information of the plant at the start of the time windows. In MPC, a sufficiently accurate model and the information of the current status of the systems are required. Therefore, different from RBPCS in Section 3.1 that only required driving distance and SOC, the optimization-based method requires the model and parameters of the vehicle.

The prediction horizon, N_p, is how far we wish to predict the future, whereas a vector called control horizon, N_c, that contains the variation of inputs in order to reach the desired trajectory of outputs. In the planning process, we need the state variables at each time step in order to predict the future, which is either directly measured or estimated. A good dynamic model will give an accurate and consistent prediction of the future (Wang, 2009). Furthermore, DP is applied to decide the optimal engine-on time by calculating the cost function defined in the prediction horizon of MPC. An MPC is employed for fuel consumption minimization, formulated as a constrained nonlinear optimization problem, and solved by DP at each time step. To implement MPC, the model of PHEV and battery should be obtained. From the torque for vehicle (3), we can obtain the torque of the electric motor that is expressed by

$$T_{em} = \frac{1}{\eta_{em} N_{em}} \left(T_{drive} - \eta_{eng} N_{eng} S_{eng} T_{eng} \right). \tag{17}$$

From (9) and (10), the power of battery can be given as

$$P_b = \frac{1}{N_{em} \eta_{em}} \left(T_{drive} - \eta_{eng} N_{eng} S_{eng} T_{eng} \right) \omega_{em}. \tag{18}$$

Thus, the model of battery in (5) becomes

$$\frac{dSOC}{dt} = \frac{-V_{oc} + \sqrt{V_{oc}^2 - 4\left[\frac{1}{\eta_{em} N_{em}} (T_{drive} - \eta_{eng} N_{eng} T_{eng} S_{eng}) \omega_{em}\right] R_b}}{2 R_b Q_b}. \tag{19}$$

The model of fuel consumption is written as

$$m_f(k+1) = fuel(T_{eng} S_{eng}, \omega_{eng}) + m_f(k). \tag{20}$$

Thus, the engine on/off status is selected as control variables. By considering SOC and m_f as the state variables, S_{eng} as the control input, and m_f are the output, the powertrain model can be represented by (19) and (20). By defining $S_{eng}=\{0,1\}$ as the on/off status of the engine, the control input is a sequence of engine status for the prediction horizon that

$$u = S_{eng} = \left\{ S_{eng}[k], S_{eng}[k+1], \cdots, S_{eng}[k+N_p-1] \right\}, \tag{21}$$

where

$$S_{eng}[k] = \begin{cases} \{0,1\} & if \quad k < N_c \\ 0 & if \quad k \geq N_c \end{cases} \tag{22}$$

Hence, the combination of engine on/off status for the control horizon, N_c, is 2^{N_c}. With the considered model, the cost function $J(k)$ is formulated as

$$J(k) = \sum_{i=1}^{N_c-1} w_1 [m_f(k+1)]^2 + \sum_{i=1}^{N_p-1} w_2 [(SOC_{ref}(k) - SOC(k)]^2 + \sum_{i=1}^{N_c-1} w_3 [S_{eng}(k+i+1) - S_{eng}(k+i)]^2, \tag{23}$$

where N_p is the prediction horizon, w_1, w_2 and w_3 are weighting, and SOC_{ref} is SOC reference which is considered as a linear function decreasing with respective to time. In the right side of equal signs of (23), the first term of the cost function is fuel rate, the second term is SOC tracking error, and the third term is the penalty that engine often changes its on/off state. The reason of taking the third term into account is that switching the engine on and off too frequently is harmful to engine and exhaust emissions. This term is utilized as penalty term to reduce switching enring status. In the system, the states of the engine and motor have to satisfy the following physical constraints

$$SOC_{min} \leq SOC \leq SOC_{max}, \; T_{eng}^{min} \leq T_{eng} \leq T_{eng}^{max}, \tag{24}$$

$$T_{mot}^{min} \leq T_{mot} \leq T_{mot}^{max}, \; \omega_{eng}^{min} \leq \omega_{eng} \leq \omega_{eng}^{max}, \tag{25}$$

$$\omega_{mot}^{min} \leq \omega_{mot} \leq \omega_{mot}^{max}, \; P_b^{min} \leq P_b \leq P_b^{max}. \tag{26}$$

By following the control strategy, the engine will be turned on and off, by using MPC and DP with the design of the cost function J. Moreover, if the engine has to be turned on, it is operated in the high efficiency area which could provide better power consumption and less exhaust emissions. When the engine is on, the motor is control to either assist the engine or charge the battery according to the required driving torque.

Exponential-Based Prediction (EBP)

The proposed optimization-based method by using MPC requires the information of velocity at all driving instance. If the power management is tested by using standard driving cycles, required power, distance, and velocity during the entire driving cycle are available. However, in practice it is difficult to get velocity information for the future time. Thus, velocity prediction of the vehicle is mandatory in using OBPCS.

The first velocity prediction is adoped from Sun *et al.* (2015) by using exponential-based prediction (EBP). The velocity prediction is given as

$$V_{pre}(k+i) = V_{pre}(k)\times(1+\varepsilon)^i, i = 1, 2, \ldots, N_p - 1, \quad (27)$$

where $V_{pre}(k)$ is the current velocity from the vehicle, i is the prediction instance at discrete time, $V_{pre}(k+i)$ is the predict velocity within the prediction horizon N_p, and ε is predction variation constant, which is fixed between -0.05 to 0.05. The basic idea of EBP results from that vehicle velocity only varies slightly with times. Therefore, the current velocity commanded by the driver is considered to decrease and increase gradually afterwards, and the variation of prediction can be tuned by selecting the constant ε. Consequently, the required velocity information in N_p future instance can be obtained from (27). By utilizing this method, the velocity can be roughly predicted without taking history data and other driving information into account with better computational efficiency, but the accuracy of EBP could be degraded.

Neural Network Prediction (NNP)

In addition to EBP, neural network is also applied to estimate the velocity of vehicle in a driving cycle. In this subsection, we propose a neural network prediction (NNP) to obtain vehicle velocity for MPC in OBPCS. Back-propagation network (BPN) is taken to build the neural network for velocity prediction. The back-propagation equations in BPN provide a way to compute the gradient of the cost function (Reed and Marks, 1999). It is a kind of feedforward neural network with a supervised learning algorithm such as stochastic gradient descent, in which we compute the gradient for many training examples.

In BPN, the j^{th} neuron in the n^{th} layer is obtained from the nonlinear function of output of the $(n-1)^{th}$ layer that

$$y_j^n = f(net_j^n), \quad (28)$$

where y^n is the output of the n^{th} layer, f is the activation function, net_j is the output of $(n-1)^{th}$ layer from weighted input which is expressed by

$$net_j^n = \sum w_{ji}^n y_j^{(n-1)} - b_j^n, \quad (29)$$

where w^n is weight between neuron j in the n^{th} layer to the i^{th} neuron in the $(n-1)^{th}$ layer, b_j^n is the bias for neuron j in layer n. The main objective of BPN is to reduce the error between the network output and the desired output. The error function is defined by

$$E = \frac{1}{2}\sum(d_k - y_k)^2, \quad (30)$$

where d_k is the output of the k^{th} neuron in the desired output, and y_k is neuron k from the network output. The learning process of the neural network is to minimum the error function E. The optimum solution for minimized E to gradient algorithm in BPN, which is similar to the method of minimum squares. Hence, the relationship between the change of wrights and error function is given as

$$\nabla w_{ji} = -\mu\frac{\partial E}{\partial w_{ji}}, \quad (31)$$

where μ is the learning rate. More details of BPN can be referred to Reed and Marks (1999). The performance of using BPN in velocity prediction for power management in PHEVs is addressed in the next section via simulation.

RESULTS AND DISCUSSION

The proposed control strategies are implemented using the program ADVISOR in MATLAB. In the simulations, the vehicle parameters are selected according to a commercial sport utility vehicle (SUV) where the vehicle mass is 2000kg, the engine maximum power is 89kW, the electric motor maximum power is 120kW, and the battery capacity is 11.5kWh. The simulation results of the proposed RBPCS and OBPCS are implemented in this section with comparisons to an engine on/off strategy developed by Zhang in (Zhang *et al.*, 2012) and EV-CS strategy. The EV-CS strategy is that PHEV starts in EV mode and switches to CS mode after the battery has reached its minimum SOC threshold. With among these four strategy, EV-CS strategy, Zhang's strategy, RBPCS, and OBPCS, EV-CS is the only strategy that requires no trip information. However, Zhang's strategy and RBPCS required the power and trip distance to decide engine on/off threshold. The proposed optimization-based strategy, OBPCS, requires power, velocity, and vehicle parameters to implement MPC.

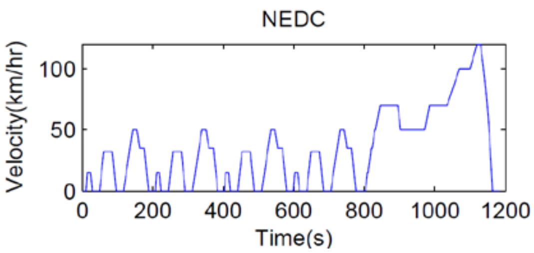
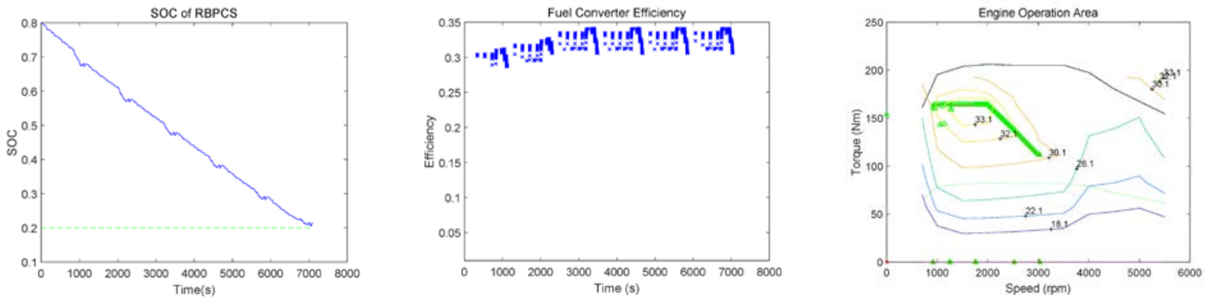


Fig. 4. Driving cycle New European Driving Cycle (NEDC).

The driving cycle considered in the simulations is New European Driving Cycle (NEDC), a driving cycle that was proposed to represent the typical usage of a car in Europe, as shown Figure 4. In order to demonstrate the performance of the proposed MPC strategy, the simulation results are conducted for 6 NEDC which are longer than pure electric range of the PHEV. Therefore, pure EV mode driving have to switch to CS mode to archive the desired driving trip.

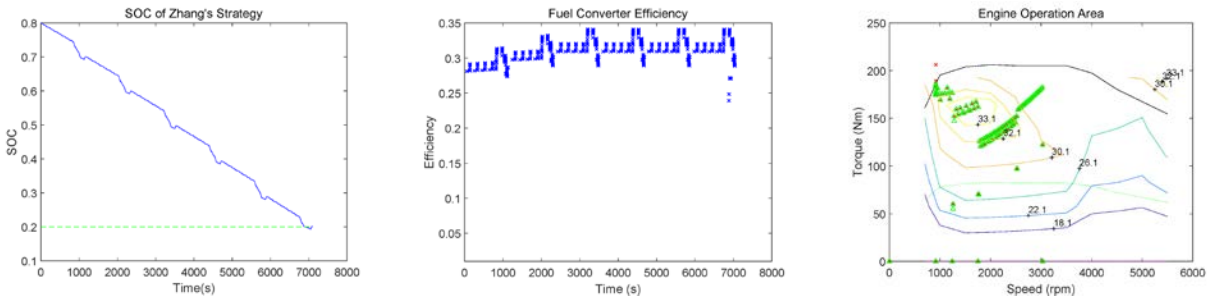
Rule-Based Proportional Control Strategy (RBPCS)

We first address the simulation results of the proposed rule-based method, RBPCS. The simulation results for 6 NEDC are illustrated in Figure 5. It can be observed that the SOC trajectories, as shown in Fig. 5 (a), using the proposed RBPCS for NEDC are operated in CD mode, which has been demonstrated the best driving mode for PHEVs. Fig. 5 (b) illustrates the engine operating efficiency of RBPCS. We can see that with Algorithm 1, the engine always operates at the best efficiency with desired velocity because SOC for the entire trip is larger than SOC_{min}. The corresponding engine operating area for RBPCS in NEDC are shown in Fig. 5 (c), which provide operating torque and engine speed.



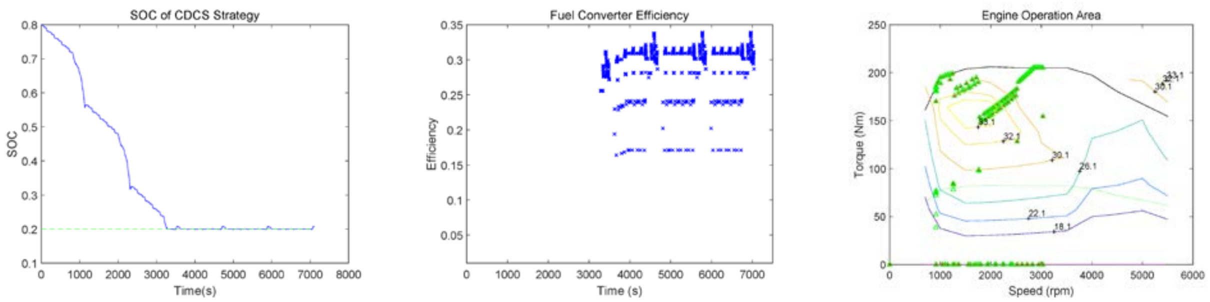
(a) SOC trajectory (b) Engine operating efficiency (c) Enginer operating area (efficiency)

Fig. 5. Simulation results using the proposed RBPCS.



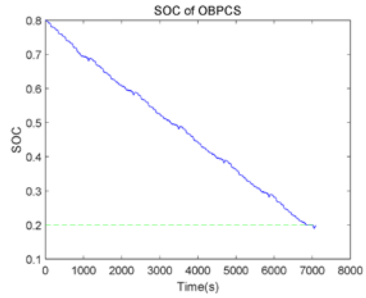
(a) SOC trajectory (b) Engine operating efficiency (c) Enginer operating area (efficiency)

Fig. 6. Simulation results of the power management proposed in (Zhang *et al.*, 2012).

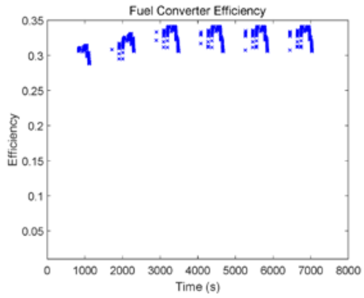


(a) SOC trajectory (b) Engine operating efficiency (c) Enginer operating area (efficiency)

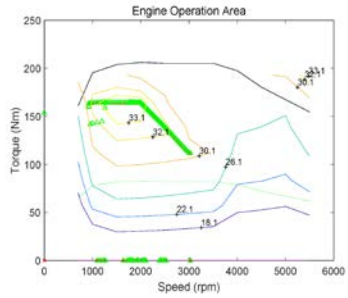
Fig. 7. Simulation results using EV-CS strategy.



(d) SOC trajectory



(e) Engine operating efficiency



(f) Enginer operating area (efficiency)

Fig. 8. Simulation results using the proposed OBPCS for 6 NEDC.

Table 1. Fuel consumton, equivalent fuel consumption, final SOC level for comparisons to the proposed RBPCS

Driving Cycle	Control Strategy	Fuel Consumption (L/100km)	Equivalent Consumption (kWh/100km)	Final SOC Level	Fuel Improvement
6 NEDC	RBPCS	4.9219	54.0848	0.2127	21.87%
	Zhang's method	5.1319	56.1597	0.2011	18.54%
	EV-CS mode	6.2999	66.4495	0.2069	-

Table 2. Fuel consumton, equivalent fuel consumption, final SOC level utilizing the proposed OBPCS

6 NEDC	Fuel Consumption (L/100km)	Equivalent Consumption (kWh/100km)	Final SOC Level	Fuel Improvement
Known Trip Velocity	4.8641	53.8458	0.1970	22.79%
EBP (ε=0.05)	5.0959	55.9081	0.1970	19.11%
EBP (ε=0)	4.9212	54.3433	0.1976	21.88%
EBP (ε=-0.05)	4.9433	54.5382	0.1977	21.53%
NNP (Neural Network)	4.8832	54.0035	0.1977	22.49%
EV-CS mode	6.2999	66.4495	0.2069	-

To demonstrate the performance and efficiency of the proposed RBPCS, we implemented the vehicle model with identical trip by using previously developed engine on/off method (Zhang *et al.*, 2012) and basic EV-CS mode. The results for Zhang's method (Zhang *et al.*, 2012) are shown in Figure 6, whereas the simulation results using EV-CS mode are illustrated in Figure 7. From Fig. 6 (a), we can observe that Zhang's methods can also guarantee a CD mode trajectory in PHEVs. However, the engine cannot always operate at the best efficiency when it is turned on. Moreover, when the engine is on, it doesn't operate at the best efficiency by observing Fig. 6. For EV-CS mode, it can be seen from Fig. 7 (a) that the SOC trajectories are not in pure CD mode, so the fuel consumption inefficient. After the SOC trajectory drops to SOC_{min}, the engine have to be turned on to both drive the vehicle and charge the battery. Therefore, the engine operating efficiency is worse and the engine cannot be operated at the best regions, as illustrated Fig. 7 (c).

The comparison results between the proposed rule-based method, and previously developed algorithm are shown in Table 1. We can conclude that with 6 NEDC, the proposed RBPCS not only have best fuel consumption, but also generate satisfactory equivalent consumption. Moreover, by comparing to EV-CS mode, the proposed RBPCS can guarantee about 20% fuel improvement which is better than the previous method (Zhang *et al.*, 2012).

Optimization-Based Prediction Control Strategy (OBPCS)

The proposed optimization-based engine on/off strategy is implemented via simulation subsequently in this section. Since the proposed MPC strategy requires the trip information and vehicle velocity, which is difficult to obtain in practice, the exponential-based prediction (ESP) is first considered, and then the neural network prediction (NNP). The weights selected for the cost function (23) are w_1 = 0.007, w_2 = 560 for NEDC. The engine on/off penalty weight is given as w_3 = 0.5. The simulation results using OBPCS and ESP for 6 NEDC are shown in Figure 8. It can be observed that by using MPC the engine will be turned on only when the required torque is high. When the required torque is low, the engine is off and the vehicle is driven solely by electric motor. The SOC trajectories of the proposed OBPCS for 6 NEDC are shown in Fig. 8 (a). It can be seen that the SOC is near the SOC reference. The engine efficiency and operation points are illustrated in Fig.s 8 (b) and 8 (c), respectively. It can be seen that the engine is operated at high efficiency during the driving cycle so that the fuel economy is improved.

In this paper, neural network is also utilized to predict vehicle velocity. The driving cycle NEDC is utilized as the neuron to train the neural network so as to to train the weights in the cost function (23). The driving status, e.g. duration, distance, average velocity, and average acceleration are considered as the inputs to train neural network so that w_1 and w_2 can be selected to guarantee a better SOC trajectory. The engine on/off weight is fixed to w_3=0.5. The fuel consumption with respect to weights w_1 and w_2 are shown in Figure 9. The fuel consumptions in the simulation results with OBPCS are summarized in Table 2. The weights for EBP are selected the same as in the previous case. Since velocity prediction from EBP can be varied with different constant ε, we show some results in the same table to see the tendency. It can be observed from the table that optimization-based method OBPCS are always better than RBPCS and Zhang's method because the fuel improvements comparing to EV-CS mode using OBPCS are always around 20%. We also observe that if less information is available, EBP can provide satisfactory performance by using OBPCS.

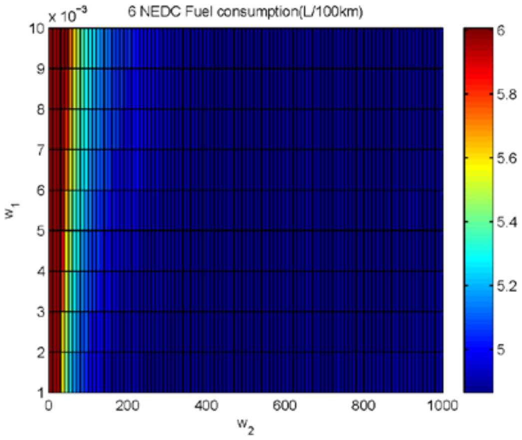


Fig. 9. Fuel consumption with respect to weights w_1 and w_2 from Neural Network for the distribution of fuel consumption.

CONCLUSION

In this paper, a rule-based and an optimization-based power management strategies for PHEVs are developed by using the engine on/off status. For the rule-based method (RBPCS), the engine on/off threshold P_s is decided so that the engine is operated at the best efficiency when it is turned on. A proportional method is utilized with the information of trip distance to guarantee that the SOC trajectory drops to SOC_{min} at the end of a trip. Since P_s is decided dynamically and the engine only operates at the best efficiency with the desired vehicle velocity, the fuel consumption and vehicle performance are shown to be better than previously proposed method. Subsequently, an optimization-based method (OBPCS) is proposed by using MPC and DP to decide the engine on/off status. A sequence of engine status Seng is first decided by MPC to ensure that SOC tracks the reference (keeping CD mode for the entire duration). With the utilization of EBP and NNP for velocity prediction, we have demonstrated that OBPCS is superior to the strategy using the engine on/off threshold and CD-CS mode. In the future, we will improve the proposed method to guarantee that fuel consumption and performance can be improved with less information about a trip so that the proposed strategy can be implemented in practice. Moreover, emissions and equivalent fuel consumption are also worth to study in the research and development of PHEVs.

ACKNOWLEDGEMENT

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REFERENCES

Borhan, H., Vahidi, A., Phillips, A. M., Kuang, M., Kolmanovsky, I. V., and Cairano, S. D. (2012). MPC-based energy management of a power-split hybrid electric vehicle. *IEEE Transactions on Control Systems Technology* **20**, **3**, 593–603.

Borhan, H. A., Vahidi, A., Phillips, A. M., Kuang, L., and Kolmanovsky I. V. (2009). Predictive energy management of a power-split hybrid electric vehicle. *American Control Conference* 3970–3976.

Cai, Y., Ouyang, M., and Yang, F. (2017) Energy management and design optimization for a series-parallel PHEV city bus. *International Journal of Automotive Technology* **18**, **3**, 473–487.

Chen, Z., Mi, C. C., Xia, B., and You, C. (2014a). Energy management of power-split plug-in hybrid electric vehicles based on simulated annealing and Pontryagin's minimum principle. *Journal of Power Sources* **272**, 160–168.

Chen, Z., Mi, C. C., Xiong, R., Xu, J., and You, C. (2014b). Energy management of a power-split plug-in hybrid electric vehicle based on genetic algorithm and quadratic programming. *Journal of Power Sources* **248**, 416–426.

Chen, Z., Mi, C. C., Xu, J., Gong, X., and You, C. (2014c). Energy management for a power-split plug-in hybrid electric vehicle based on dynamic programming and neural networks. *IEEE*

Transactions on Vehicular Technology **63**, **4**, 1567–1580.

Emadi, A., Ehsani, M., and Miller, J. M. (2003). *Vehicular Electric Power Systems: Land, Sea, Air, and Space Vehicle*s. CRC Press.

Feng, T., Yang, L., Gu, Q., Hu, Y., Yang, T., and Yan, B. (2015). A supervisory control strategy for plug-in hybrid electric vehicles based on energy demand prediction and route preview. *IEEE Transactions on Vehicular Technology* **64**, **5**, 1691–1700.

Frank, A. A. (2007). Plug-in hybrid vehicles for a sustainable futuer. *American Scientist* **95**, **2**, 158–165.

Gong, Q., Li, Y., and Peng, Z. R. (2008). Trip-based optimal power management of plug-in hybrid electric vehicles. *IEEE Transactions on Vehicular Technology* **57**, **6**, 3393–3401.

Hsieh, Y.-M. and Liu, Y.-C. (2015). Model predictive control strategy for plug-in hybrid electric vehicles. *International Conference on Control, Automation, Robotics & Vision*.

Hwang, J.-J., Hu, J.-S., and Lin, C.-H. (2015). Design of a range extension strategy for power decentralized fuel cell/battery electric vehicles. *International Journal of Hydrogen Energy* **40**, **35**, 11704–11712.

Khayyer, P., Wollaeger, J., Onori, S., Marano, V., Özgüner, Ü., and Rizzoni, G. (2012). Analysis of impact factors for plug-in hybrid electric vehicles energy management. *International IEEE Conference on Intelligent Transportation Systems* 1061–1066.

Kimura, A., Ando, I., and Itagaki, K. (2005). Development of hybrid system for SUV. *SAE Technical Paper* 2005–01–0273.

Liu, C. and Murphey, Y. L. (2014). Power management for plug-in hybrid electric vehicles using reinforcement learning with trip information. *IEEE Transportation Electrification Conference and Expo*.

Marcos, D. and Bordons, C. (2012). Power management of a plug-in hybrid electric vehicle based on cycle energy estimation. *IFAC Workshop on Engine and Powertrain Control, Simulation and Modeling* 363–370.

Matthe, R. and Eberle, E. (2014). *The Voltec System-Energy Storage and Electric Propulsion*, Elsevier: Amsterdam, The Netherlands, 2014.

Moon, P., Burnham, A., and Wang, M. (2006). Vehicle-cycle energy and emission effects of conventional and advanced vehicles. *SAE Technical Paper* 2006–01–0375.

Qi, Y., Xiang, C., Wang, W., Wen, B., and Ding, F. (2018). Model predictive coordinated control for dual-mode power-split hybrid electric vehicle. *International Journal of Automotive Technology* **19**, **2**, 345–358.

Reed, R. D. and Marks II, R. J. *Neural Smithing: Supervised Learning in Feedforward Artificial Neural Networks*. MIT Press, 1999.

Sun, C., Hu, X., Moura, S. J., and Sun, F. (2015). Velocity predictors for predictive energy management in hybrid electric vehicles. *IEEE Transactions on Control Systems Technology* **23**, **3**, 1197–1204.

Taghavipour, A., Azad, N. L., and McPhee, J. (2012). An optimal power management strategy for power split plug-in hybrid electric vehicles. *International Journal of Vehicle Design* **60**, **3/4**, 286–304.

Tanoue, K., Yanagihara, H., and Kusumi, H. (2008). *Hybrid is a Key Technology for Future Automobiles*, Springer-Verlag Berlin Heidelberg.

Wang, L. (2009). *Model Predictive Control System Design and Implementation Using MATLAB*.

Williamson, S., Lukic, M., and Emadi, A. (2006). Comprehensive drive train efficiency analysis of hybrid electric and fuel cell vehicles based on motor-controller efficiency modeling. *IEEE Transactions on Power Electronics* **21**, **3**, 730–740.

Wirasingha, S. G. and Emadi, A. (2011). Classification and review of control strategies for plug-in hybrid electric vehicles. *IEEE Transactions on Vehicular Technology* **60**, **1**, 111–122.

Wu, G., Boriboonsomsin, K., and Barth, M. J. (2014). Development and evaluation of an intelligent energy-management strategy for plug-in hybrid electric vehicles. *IEEE Transactions on Intelligent Transportation Systems* **15**, **3**, 1091–1100.

Yin, D. and Hu, J.-S. (2014). Active approach to electronic stability control for front-wheel drive in-wheel motor electric vehicles. *International Journal of Automotive Technology* **15**, **6**, 979–987.

Zhang, B., Mi, C. C., and Zhang, M. (2011). Charge-depleting control strategies and fuel optimization of blended-mode plug-in hybrid electric vehicles. *IEEE Transactions on Vehicular Technology* **60**, **4**, 1516–1525.

Zhang, C. and Vahidi, A. (2012). Route preview in energy management of plug-in hybrid vehicles. *IEEE Transactions on Control Systems Technology* **20**, **2**, 546–553.

Zhang, J. and Shen, T. (2014). Nonlinear mpc-based power-assist scheme of internal combustion engines in plug-in hybrid electric vehicles. *European Control Conference* 1164–1169.

Zhang, J., Shen, T., Sawada, T., and Kubo, M. (2014). Nonlinear mpc-based power management strategy for plug-in parallel hybrid electrical vehicles. *Chinese Control Conference* 280–284.

Zhang, M., Yang, Y., and Mi, C. (2012). Analytical approach for the power management of blended-mode plug-in hybrid electric vehicles. *IEEE Transactions on Vehicular Technology* **61**, **4**, 1554–1566.

基於引擎啟動門檻之插電混合動力車輛動力管理策略

謝一民　　劉彥辰
國立成功大學 機械工程學系

摘 要

插電式混合動力車為新形態之油電混合動力車輛，具有較大之馬達動力和電池容量。插電式混合動力車之動力來源通常以馬達為主，再輔以燃油引擎進行長距離且較低油耗之駕駛。為了讓插電式混合動力車輛在不同環境與駕駛距離下，具有最佳的性能和油耗，混合動力控制策略成為一個重要的因素。本研究基於引擎啟動門檻控制策略，首先藉由所剩駕駛距離與電池電量，以比例控制器調節引擎啟動門檻，使插電式混合動力車輛能夠在一段行程中完全使用 Charging-depleting(CD)模式，達成保持性能且降低油耗之目標。隨後，本研究裡用模型預測能量管理控制策略，藉由模型預測與動態規劃控制引擎啟動，並使用了指數變化與類神經網路預測車速，以提高本研究提出方法再實際應用的可行性。